Motor Control Information Extracted from Surface EMG as Muscle Force Estimation

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Abstract: The aim of this paper is to introduce an extension to a force estimation technique based on activity index and to compare it to two other muscle force estimation techniques that also use the motor control information on the same set of surface EMG signals. Our new method is called motor unit twitch force technique and the compared methods include motor unit action potential rate and activity index. The main difference of the three compared methods lies in the extraction of the motor control information from multi-channel surface EMG. Motor unit action potential rate and activity index measure global muscle activity as they represent the summation of innervation pulse trains of all active motor units, while twitch force technique decomposes the surface EMG and obtains the activity of all active individual motor units separately. This means a great improvement over activity index and motor unit action potential rate methods as both force regulation principles, i.e. motor unit recruitment and firing rate modulation can be observed. Surface EMG signals used in the experiment were recorded from biceps brachii muscle during elbow flexion on five subjects. Two-dimensional matrix of surface electrodes (13 rows by 5 columns) was applied. Isometric constant force contractions at three different force levels were performed, i.e. at 5, 10 and 30 % of maximal voluntary contraction. Torque produced at the elbow joint was measured simultaneously with surface EMG. The force estimation error of the methods was measured by root mean square error between the recorded and estimated force. Our new motor unit twitch force technique reduced the muscle force estimation error significantly, for 13% when compared to the motor unit action potential rate, and for 2% when compared to the activity index method.

Key-Words: surface electromyography, muscle force estimation, EMG force relationship, MUAP rate, activity index, twitch force

1 Introduction

Surface electromyography (sEMG) is an important tool in various research fields, including biomechanics and kinesiology, where it is used to understand how joints are loaded, passive tissues are stressed and muscles are activated under different working conditions [1]. Recently the use of sEMG has been studied also in man-machine interaction for an intelligent machine control [2].

SEMG has been used for over fifty years as a non-invasive method for measuring muscle activity during voluntary contractions. It is a measure of the depolarization of muscle fibres, and when the sEMG signal is treated properly, it can be used as an indirect measure of muscle activity or force [1].

Muscle force estimated from sEMG is an indicator of dynamic changes in muscle activity and can be used for the control of limb prostheses [27], in the diagnosis of neuromuscular diseases, in the studies of the motor control system and in fundamental studies of muscle mechanics [17]. Advanced force estimation techniques can also be used in the forward-dynamics biomechanical models that estimate muscle forces, joint torques and ligament forces from sEMG [18]. Models for various joints have been already presented, for the ankle [16], the knee [19], etc.

Force production in a muscle is regulated by the central nervous system, which controls two main mechanisms, i.e. the recruitment and derecruitment of motor units (MUs) and the modulation of their discharge rates [12]. The greater the number of MUs recruited and their discharge frequencies, the greater the force that will be exerted by the muscle. The same two mechanisms determine also the electrical activity in a muscle. Thus, a direct relationship between the sEMG and exerted muscle force might be expected [3].

Various force estimation techniques were introduced in the literature: force estimation using artificial neural networks (ANN) [13], sEMG amplitude processing [14], motor unit action potential (MUAP) rate [9], [10] and the activity index [6].

Liu et al. [13] used an ANN to study sEMG-force relationship. At first the sEMG-force relationship was determined from the recorded sEMG signals and muscle forces. This relationship was then used to predict muscle forces of the subjects whose sEMG and force data were not used for the relationship derivation. The reported root mean square error (RMSE) of their estimation is less than 15 %, so the ANN can be used for sEMG based muscle force prediction.

Amplitude processing techniques are still the most widely used; they consist of signal rectification followed by low-pass filtering of the rectified signal, such as average rectified or root mean square values [15].

Milner-Brown et al. [14] introduced a sEMG amplitude processing technique for force estimation. In their experiments sEMG signals of the first dorsal interosseus muscle were recorded and rectified. The contribution of the two force generation mechanisms was studied as well. They found that the largest contribution of MU recruitment occurs at low force levels, while the contribution due to increased firing rate is dominant at higher force levels.

Advanced sEMG amplitude processing techniques were also developed using multi-channel sEMG [4], high-pass filtering [5] and multi-channel signal whitening [15]. Staudenmann et al. [4] improved standard amplitude processing technique by using multi-channel sEMG signals, or high-density sEMG. Instead of using bipolar signals only they used a 2D matrix of electrodes and studied the importance of the number of electrodes for optimizing muscle force estimation. They reported that the multi-channel technique improved muscle force estimation by about 30 % when compared to a single bipolar electrode pair.

Another improvement of the classical amplitude processing technique was proposed by Potvin and Brown [5]. They used a standard bipolar electrode pair, but instead of using a high-pass filter with cut-off frequency between 10 and 30 Hz, they used much higher cut-off frequencies up to 440 Hz, They reported that filtering out 99 % of the raw sEMG signal power significantly improved muscle force estimation.

Clancy et al. [14] introduced a new concept of signal whitening in the field of sEMG based muscle force estimation. They successfully combined the multi-channel approach with signal whitening and compared their results to force estimation techniques based on amplitude processing.

The common weak point of all the methods overviewed so far is, that the sEMG amplitude is influenced not only by motor control aspects, but also by peripheral properties of the muscle, such as MU size, position (deep or superficial) and recording setup parameters (placement of the surface electrodes). All these issues aggravate the force estimation process [9]. Therefore methods based on motor control information were introduced, such as MUAP rate [9] and activity index [6] that are described in Section 2.

Muscle activity [6, 28] and exerted muscle force are two closely related phenomena; however muscle activity identification is a basic task, while only global muscle activity is observed. In contrast, muscle force estimation is more advanced, as an exact increase or decrease of the generated force is obtained. Panjkota et al. [28] introduced a muscle activity measure, similar to the activity index [6]. They carried out a study of muscle activity during ergometer rowing, where EMG signals were recorded simultaneously with kinematics data. EMG signals were denoised using wavelets and rectified. Finally the muscle activity was defined by applying a threshold to the rectified EMG signals.

A theoretical background and a mathematical model for muscle force generation by individual MUs was introduced by Fuglevand et al. [12]. A common problem to all force estimation techniques is that forces are estimated indirectly because direct non-invasive measurements of individual muscle forces are generally neither possible nor practical [1].

The rest of our paper is organized as follows. Section 2 presents methods used including experimental protocol and three force estimation techniques based on motor control information. We present our new force estimation approach using MU twitch force technique and compare results to two other methods of MUAP rate and activity index. Section 3 gives the experimental results and shows the differences among the compared methods. Section 4 discusses the approaches and results, while the last section concludes the paper.

2 Methods

2.1 Experimental protocol

Five young healthy male subjects participated in the experiment. SEMG signals were recorded using a matrix of 61 electrodes arranged in 5 columns and 13 rows (Fig. 1). Inter-electrode distance was set to 5 mm. The electrode pins (diameter 1.27 mm; RS 261-5070, Milan, Italy) were spring loaded telescopic to adapt to the skin surface (Fig. 1).

Fig. 1: Two-dimensional matrix (13 rows and 5 columns) of surface electrodes used for sEMG acquisition.

Recordings were performed in a single differential configuration during isometric, constant-force contractions of the dominant biceps brachii muscle. The matrix was connected to four 16-channel EMG amplifiers (LISiN; Prima Biomedical & Sport, Treviso, Italy). The sEMG signals were amplified, band-pass filtered (3 dB bandwidth, 10-500 Hz), sampled at 2500 Hz, and converted to digital form by a 12-bit A/D converter. The four acquisition cards acquiring the signals from the matrix were driven by the same clock signal.

The experimental protocol consisted of the following steps: first, the dominant arm of the subject was placed into the isometric brace which was set to the angle of 120° (see Fig. 2). Three five-second contractions at maximum voluntary contraction (MVC) force were performed each separated by 2 minutes of rest. Using the torque sensors, the maximum contraction force was measured and averaged over all three measurements. Afterwards, a 5 minute rest was given to the subject. The skin was slightly abraded with abrasive paste and moistened to improve the electrode-skin contact. The location of the innervation zone in the dominant biceps brachii of the subject was determined from the travelling action potentials detected during voluntary low-force muscle contraction by a linear array of 16 electrodes of size 10×1 mm and the inter-electrode distance of 10 mm. Afterwards, the linear array of electrodes was removed and the skin remoistened. The matrix of 61 electrodes was placed over the distal half of dominant biceps brachii with its third electrode row centred over the estimated innervation zone and columns aligned with the muscle fibres (see recorded signals in Fig. 3).

Fig. 2: The isometric brace used to keep the elbow angle constant at 120° during the isometric acquisition of sEMG signals. Torque sensors are located at the joint of the rigidly connected parts of isometric brace.

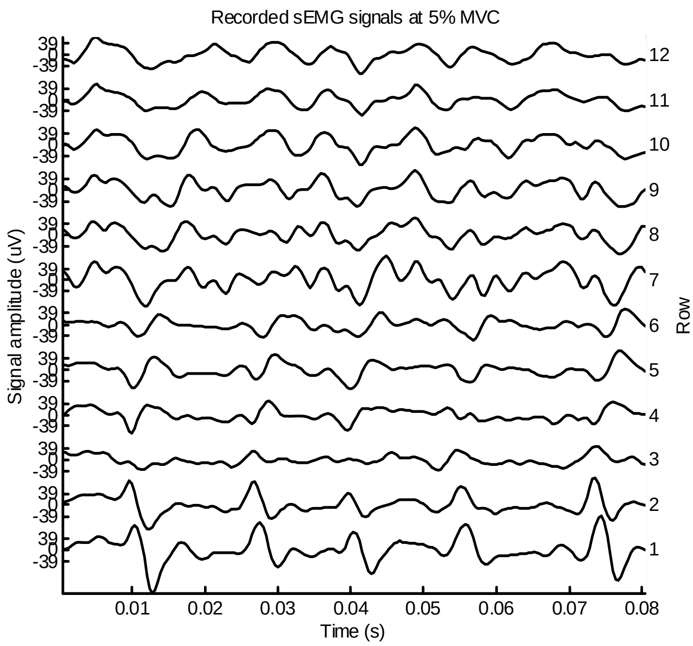

Fig. 3: SEMG signals recorded from the central (3rd) column of 2D electrode matrix are depicted. X-axis represents time, left-hand y-axis signal amplitude and right-hand y-axis the electrode row numbers. MUAP propagation among adjacent rows is easily spotted, while rows are placed longitudinally to the muscle fibres, 3rd row being the innervation zone.

The sEMG signals were recorded during 30 seconds long contractions at 3 different constant force levels, i.e. 5, 10, and 30 % MVC. The excerpt of the recording is depicted in Fig. 3 for a 5 % MVC contraction. After each contraction 10 minute rest was given to the subject. The noise and the movement artefacts were visually controlled and reduced by applying water to the skin surface. The contraction force was measured by the torque sensor and displayed on the oscilloscope to provide the visual feedback to the subjects.

2.2 MUAP rate technique

MUAP rate was introduced as a measure of the central nervous system input to the muscle [9]. The relationship between input to the muscle and exerted force was studied in [23]. Authors reported that corticospinal output does not parallel force increments across the whole contraction range. MUAP rate is obtained as the number of MUAPs per second, and equals the sum of firing rates of all active MUs in a chosen time epoch. It reflects both parameters that the central nervous system uses for motor control, i.e. the number of active MUs and their firing rate.

In this approach MUAPs are extracted from the sEMG by using the continuous wavelet transform; the details of the approach can be found in [11]. Although their algorithm uses multi-channel information for MUAP extraction, only channels from the electrodes placed longitudinally to the muscle fibres are useful, because the propagation delay of MUAPs is searched between adjacent channels. Since our measurements were recorded using 2D arrays of electrodes, only the signals from the central (3rd) electrode column were used (as depicted in Fig. 3).

The MUAP extraction approach needs some specific parameters to be set. We used the same values as those reported in [9]. The algorithm started by calculating the continuous wavelet transform of the first channel. When the scalogram reached a maximum that was higher than a user predefined threshold (set to 0.1), a candidate MUAP was indicated. The algorithm then searched for candidate MUAPs located in the surrounding channels within a time delay corresponding to conduction velocities between 2 and 8 m/s, as suggested in [11]. When the same shape was found at least in 3 adjacent channels, the candidate was considered a MUAP. Then, the wavelet transform was calculated for the next channel. The algorithm cycled through all the channels in this way. Outputs of the algorithm were the firing moments of all detected MUAPs (see Fig. 4). The number of detected firings in one-second epochs was calculated and this number stands for the MUAP rate estimation.

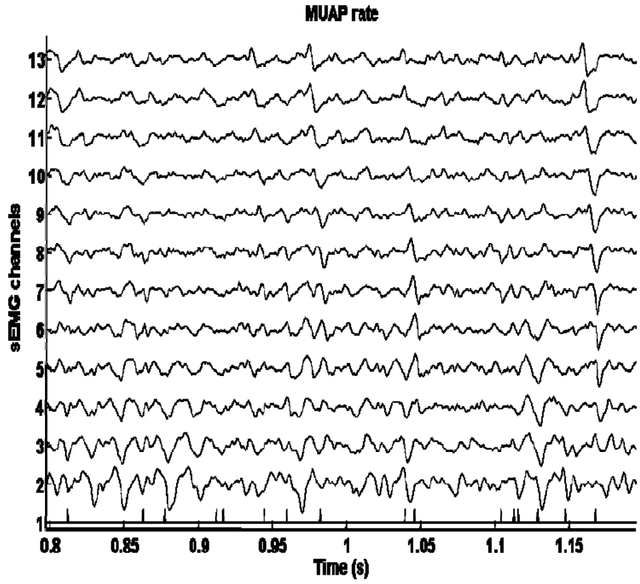

Fig. 4: Rows from 2-13 depict sEMG channels, inputted into the algorithm, while row 1 below shows the firing moments of detected MUAPs (the method output).

2.3 Activity index

The activity index is a measure of muscle activation level. It was first introduced as the first stage of the correlation-based sEMG decomposition algorithm, known as convolution kernel compensation [8, 25]. It ranges between 0 and 1, 0 being produced with no MUs active in the observed muscle, and 1 stands for the maximum activity of all MUs. Compared to the sEMG amplitude the activity index is smoother, which serves as a good basis for force estimation.

To understand the principle of activity index, the considered sEMG model is presented briefly. The most feasible model for multi-channel sEMG recordings is the discrete, shift-invariant multiple-input and multiple-output (MIMO) model [8]. Each input in such a MIMO system is considered a MU innervation pulse train (IPT) triggering the muscle, while the system responses correspond to the MUAPs as captured by the pick-up electrodes. The individual sEMG measurements represent the model outputs (see Fig. 5).

Referring to the model in Fig. 5, the *i*-th sEMG measurement can be written as:

$$x_i = \sum_{j=1}^{N} h_{ij} * s_j, \tag{1}$$

where x_i is the *i*-th sEMG measurement, s_j the innervation pulse train of the *j*-th MU, and h_{ij} the MUAP of the *j*-th MU, detected by the *i*-th electrode. The symbol * stands for convolution.

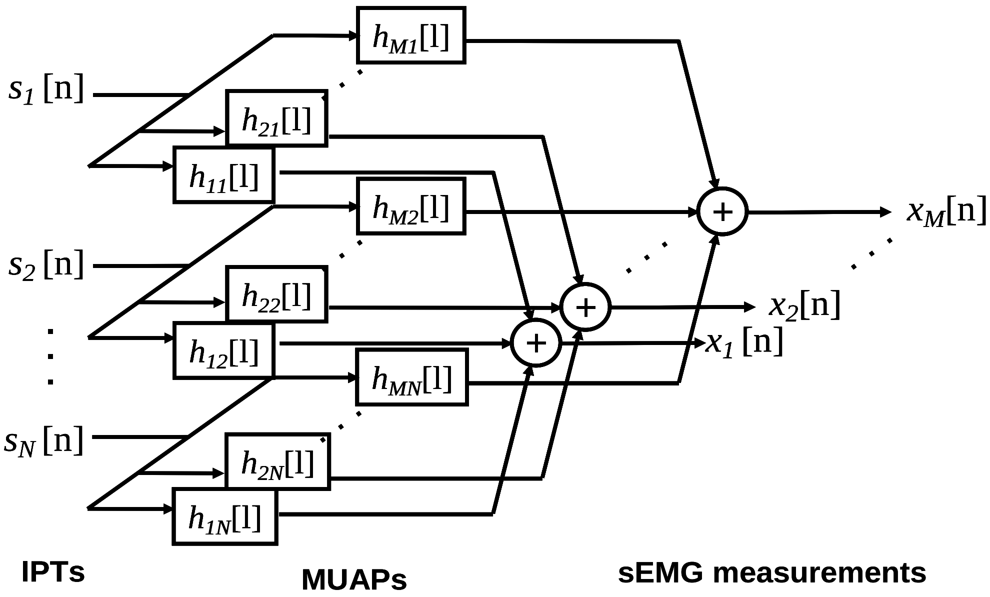

Fig. 5: Proposed multi-channel sEMG model. Left side depicts N system inputs (IPTs), N x M MUAPs stand in the middle, and on the right-hand side there are M outputs (sEMG measurements).

The system represented by Eq. (1) can be written in matrix form as:

$$\mathbf{x}(n) = \mathbf{H}\overline{\mathbf{s}}(n), \tag{2}$$

where $\mathbf{x}(n)$ is the vector of sEMG measurements, $\mathbf{H}$ stands for the MUAP matrix and $\overline{\mathbf{s}}(n)$ is the extended vector of sources.

Let N be the number of inputs (active MUs in our case) and M the number of measurements (number of recorded signals from pick-up electrodes over the muscle). Suppose the number of inputs N is smaller than the number of measurements M; then a positive integer K can be found, that satisfies the inequality $KM > N(L+K-1)$, where M is the number of measurements, N the number of inputs, L the length of MUAPs, and K an extension factor. The vector of measurements $\mathbf{x}(n)$ can be extended by K-1 delayed repetitions of each measurement. The correlation matrix of the extended measurements $\overline{\mathbf{x}}(n)$ is then calculated as:

$$\mathbf{C} = \overline{\mathbf{x}} \cdot \overline{\mathbf{x}}^T. \tag{3}$$

Multiplying the extended measurements $\overline{\mathbf{x}}(n)$ by the Moore-Penrose pseudo-inverse of the correlation matrix (Eq. (3)), we define the activity index (I_A) as:

$$I_A(n) = \overline{\mathbf{x}}(n)^T \mathbf{C}^{\#} \overline{\mathbf{x}}(n), \tag{4}$$

where symbol $^{\#}$ denotes the Moore-Penrose pseudo-inverse of the correlation matrix and ^{T} the transpose of the vector of extended measurement.

If the system represented by Eq. (2) is overdetermined, complete compensation is achieved and the activity index has a rectangular shape (see Fig. 6). Each rectangle represents the activation of an individual MUAP. The rectangle width equals the MUAP width increased by the extension factor, while the rectangle height is inversely proportional to the number of MU firings within the signal segment under observation (Fig. 6).

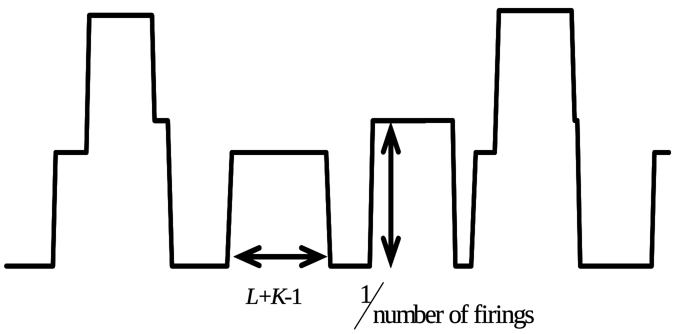

Fig. 6: The ideal activity index, when the system (2) is overdetermined.

However, when calculating the activity index of the real sEMG signals, total compensation is hardly ever achieved because of the great number of active motor units and excessive noise. In such cases, the activity index has the shape as depicted in Fig. 7. A detailed explanation of the activity index can be found in [7] and [8].

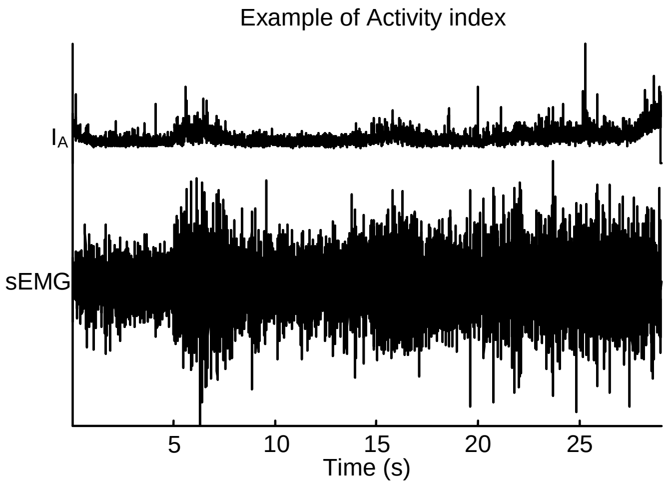

Fig. 7: Time plots of a single sEMG recording and its activity index (I_A) above show that the activity index follows the changes in sEMG, but it is much smoother.

2.4 MU twitch force technique

The MU twitch force technique is an extension of the activity index approach. Instead of calculating the global muscle activity as when using the activity index, the activity of each individual MU is obtained separately. This gives better insight into muscle properties. To make this possible, the sEMG must first be decomposed into the motor unit innervation pulse trains. Then the method combines MU twitches with MU innervation pulse trains that are extracted by the decomposition technique. The MU twitches are aligned to the IPTs and summed up to obtain the total muscle force (see Fig. 8).

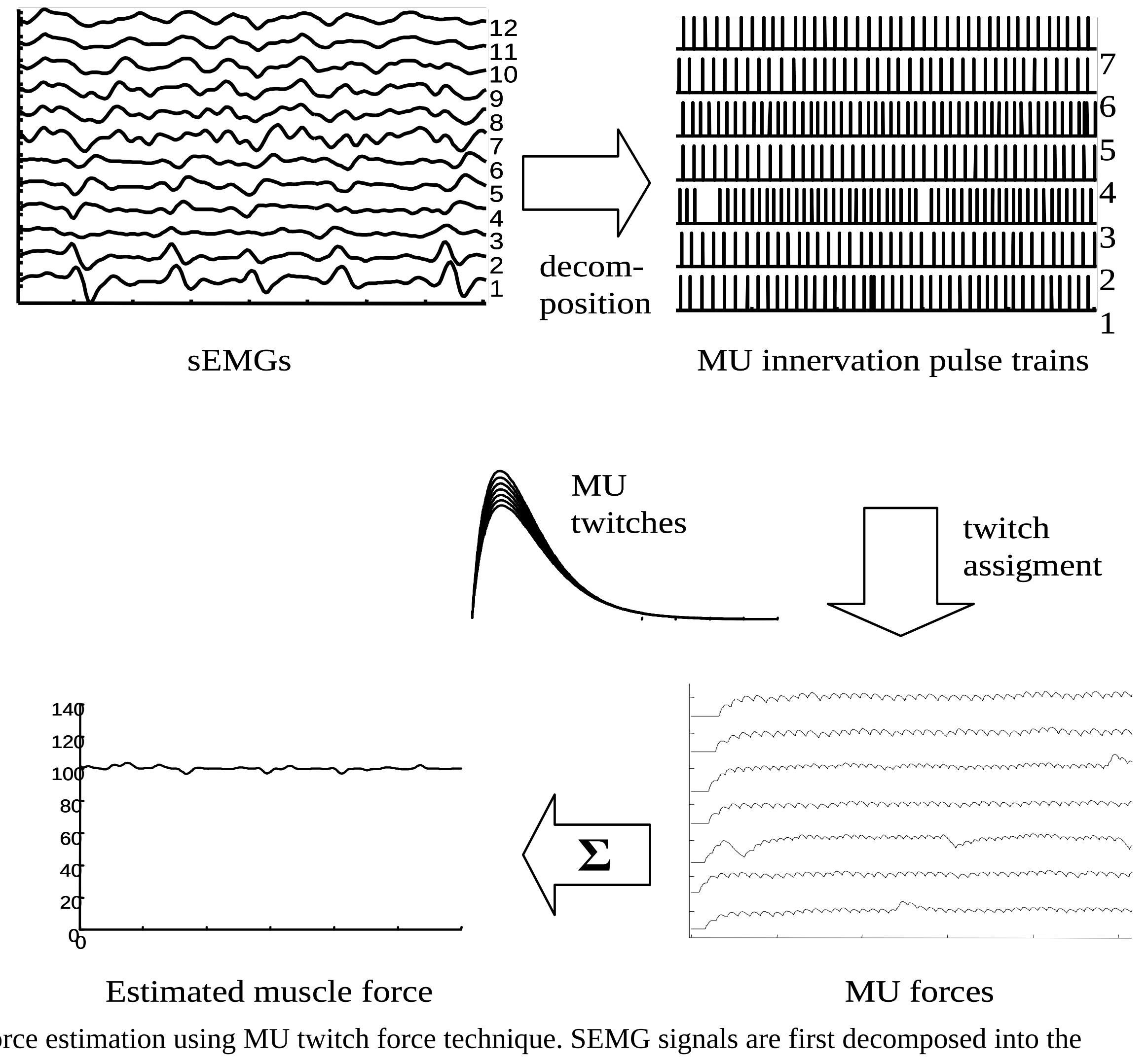

Fig. 8: Force estimation using MU twitch force technique. SEMG signals are first decomposed into the innervation pulse trains of the individual MUs. MU twitches are then aligned to IPTs, producing forces of each MU. MU forces are summed up at the end to obtain total force produced by the muscle.

This technique uses the muscle force generation model proposed by Fuglevand et al. [12]. They tested the MU pool consisting of 120 MUs. The distribution of twitch forces for the MUs was represented as an exponential function [12]. A large number of MUs produced small forces, while relatively few MUs generated large forces. Twitch force $f_i(t)$ of i-th MU was modelled as the impulse response of a critically damped, second order system [12]:

$$f_i(t) = \frac{P_i \cdot t}{T_i} \cdot e^{1-(t/T_i)}, \tag{5}$$

where T_i is contraction time to peak force of the twitch and P_i is its peak amplitude of the i-th MU. Twitch amplitudes were assigned according to their rank in the recruitment order, and twitch contraction times were inversely related to twitch amplitudes [12]. The relationship between twitch force peak amplitude (P_i) and contraction time (T_i) was approximated as:

$$T_i = T_L \cdot \left(\frac{1}{P_i}\right)^{1/c}. \tag{6}$$

The parameter T_L represents the longest twitch duration time desired for the pool, and the coefficient c is calculated as $c = \log_{RT} RP$, where RP is the range of MU peak forces and RT the range of contraction times.

The relationship between MU size, firing rate and force is studied in [21]. Henneman et al. [22] reported that MU recruitment follows an orderly sequence according to size, such that smaller slow twitch MUs are activated before larger fast twitch MUs. As more MUs are progressively recruited within a muscle, the muscle force increases. Conversely, the muscle force is reduced by deactivating motor units, which usually happens in the reverse order of their recruitment.

The range of twitch forces used in the model was 100-fold. One unit of force was equivalent to the twitch force of the first unit recruited, and the last unit recruited had a twitch force of 100 units. The range of twitch contraction times was 3-fold, the twitch of the first recruited unit having the time to peak duration of 90 ms, and for the last recruited unit of 30 ms (see Fig. 9).

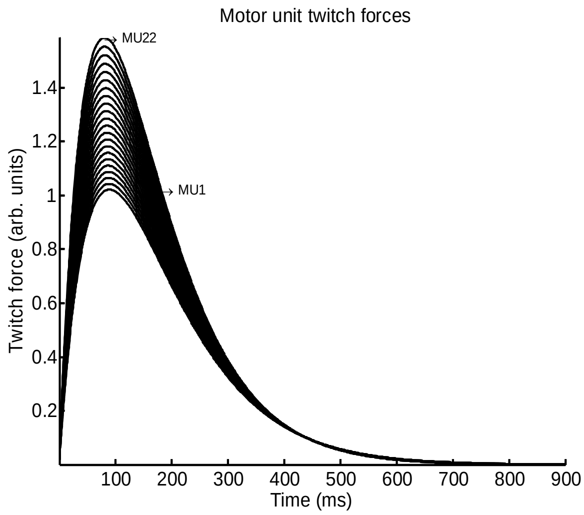

Fig. 9: MU twitches assigned to the MUs recognized by the decomposition technique.

All MUs followed the widely reported sigmoidal relationship between MU force and firing rate. If MU is driven by IPT containing k discharges, the force produced in that MU ($F_i(t)$) is equivalent to the sum of the individual twitch forces:

$$F_i(t) = \sum_{j=1}^{k} f_i(t - t_{i,j}), \qquad t - t_{i,j} \geq 0. \tag{7}$$

The value of $f_i(t - t_{i,j})$ represents the twitch response to the MU discharge j. The total force of the muscle was determined as a linear summation of all the individual MU forces:

$$F_M(t) = \sum_{i=1}^{n} F_i(t) \tag{8}$$

In our experiment, the method recognized 22 ± 5 MUs per subject (mean ± std. dev.). This number is substantially smaller than the 120 MUs proposed in [12], hence, the twitch force and twitch contraction time ranges reported in [12] had to be modified. Firstly, with recorded contractions ranging from 0 to 30 % MVC, we assumed only low-threshold units are recruited. To correlate MUs with twitch forces correctly, the recognized MU innervation pulse trains were sorted according to the recruitment order. The first recruited MU was assigned twitch force of 1 unit with contraction time of 90 ms, while the last recruited MU had a twitch force of 1.6 units with contraction time of 80 ms. Such values are assigned to the first twenty units of all 120 MUs in the model proposed in [12] (see Fig. 9).

3 Experimental results

The method performances were measured by the root mean square error (RMSE) between the real (recorded) and the estimated force in percents as

$$RMSE(\%) = \frac{\mathrm{RMS}(\mathbf{F}_{\mathbf{real}} - \mathbf{F}_{\mathbf{est}})}{\mathrm{RMS}(\mathbf{F}_{\mathbf{real}})} \cdot 100, \qquad (9)$$

where $\mathbf{F}_{\mathbf{real}}$ is the recorded force, $\mathbf{F}_{\mathbf{est}}$ is the estimated force and RMS stands for the root mean square. The RMS of an n-dimensional vector $\mathbf{F} = (F(1), F(2), \ldots, F(n))$ is calculated as:

$$\mathrm{RMS}(\mathbf{F}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} F^2(i)} \qquad (10)$$

Prior to the calculation of RMSE, the estimated and real force were smoothed by a 1st order Butterworth low-pass filter with cut-off frequency at 10 Hz. The smoothed signals were then normalized with respect to the maximum value of each signal.

The average estimation errors of all three methods are presented in Table 1. The twitch force technique proved to be the best muscle force estimator among the compared methods, producing lower estimation errors than both the MUAP rate and activity index methods. Fig. 10 depicts distributions of estimation errors for each method.

Table 1: Comparison of average force estimation errors for MUAP rate, activity index and MU twitch force technique.

	RMSE (%)	
Method	mean	std
MUAP rate	26.25	6.36
Activity index	13.75	8.43
MU twitch force	11.46	5.89

Beside average estimation errors and error distributions, estimation errors for each individual trial for all subjects are also depicted for activity index (Fig. 11), MUAP rate (Fig. 12) and twitch force (Fig. 13) methods. Five different symbols (square, triangle, star, circle and diamond) represent five subjects and they show the estimation error.

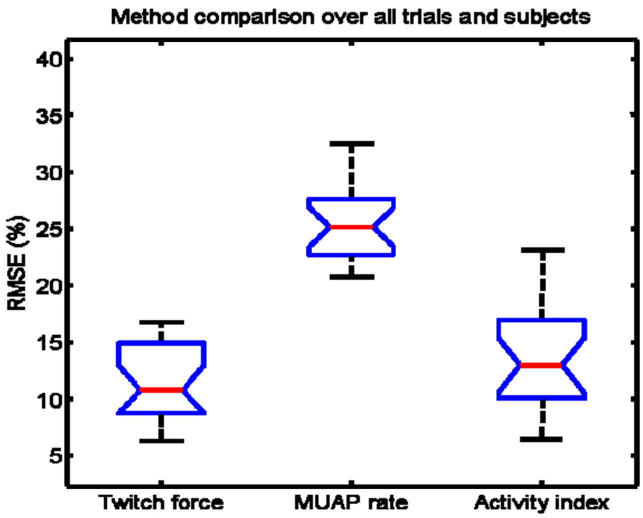

Fig. 10: Comparison of the force estimation error of all three methods on all trials and all subjects. The plot depicts median (middle line), upper and lower quartiles, whereas whiskers represent outliers.

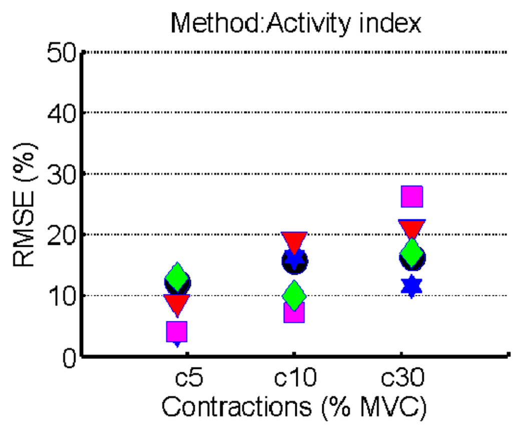

Fig. 11: The figure shows RMSE versus contraction levels for each individual trial of each subject obtained by the activity index method: the different shapes stand for different subjects.

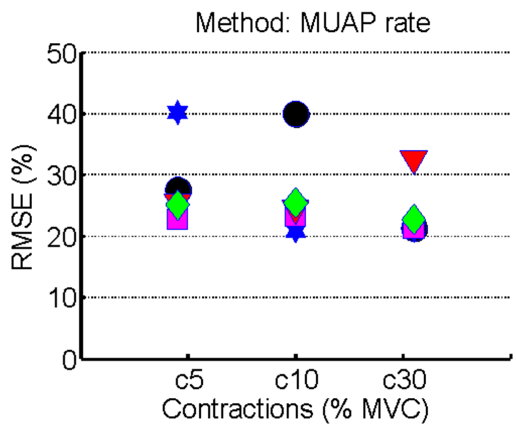

Fig. 12: The figure shows RMSE versus contraction levels for each individual trial of each subject obtained by the MUAP rate method.

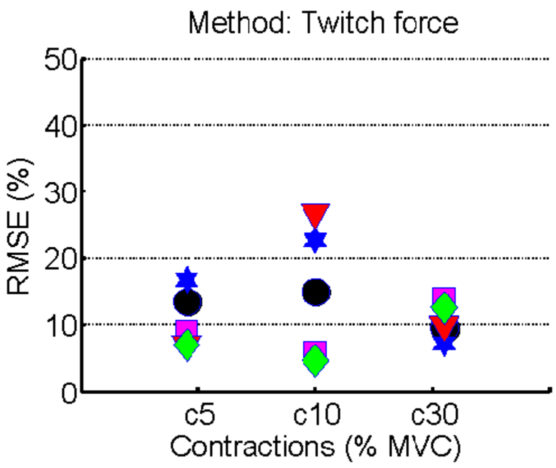

Fig. 13: The figure shows RMSE versus contraction levels for each individual trial of each subject obtained by the twitch force technique.

Along with the experiments, the execution times of all methods were compared on a PC computer with Intel P4 processor and 2 GB of RAM. The fastest method was activity index, followed by twitch force technique and MUAP rate (see Table 2). The execution times reported in the Table 2 represent the time spent for force estimation of one 30-second trial, at any level of MVC. Average times were calculated by averaging the execution times over all trials and all subjects.

Table 2: Comparison of execution times for all three methods.

	Time (s)	
Method	mean	std
MUAP rate	52.29	2.77
Activity index	10.06	0.60
MU twitch force	33.18	1.18

4 Discussion

Force estimation task is not as straightforward as it might seem. Forces or torques are usually measured externally about the joint, although they are in fact the resultant output of internal forces generated by muscles acting about the joints that they cross, as well as internal forces produced by stretching of ligaments and other passive tissues associated with the same joints [1]. As a consequence, the force of a single muscle is hardly measured and usually several muscles contribute to the detected forces [24]. Moreover, when the electrical response of muscles is measured by sEMG, only a part of the muscle and active motor units (MUs) can be detected, while measured force is actually produced by more MUs.

All three methods compared in this study are based on the principle of motor control, i.e. the number of active MUs and their firing rates, but the way the motor control information is extracted from sEMG differs for each of them. The MUAP rate extracts the number of MUAPs using the wavelet transform of multi-channel sEMG signals, while the activity index and twitch force technique use correlation-based approach instead. The MUAP rate has some drawbacks in comparison to the activity index and twitch force technique, i.e. it operates only on linear array of electrodes that must be placed longitudinally to the muscle fibres. On the contrary, activity index and twitch force technique can be calculated using the 2D matrix electrodes and, thus, considers more spatial information, which improves the muscle activity estimation.

A drawback of both methods, MUAP rate and activity index, is that only the global muscle activity (activity of all detected MUs) is observed, so the important information about which firing belongs to which MU is missing. From the point of the presented two methods, an activation of a new MU or an increase of the firing rate of an already active MU cause the same effect. But most widely accepted force models suppose each individual MU has a different force contribution [12]. From this aspect, the global muscle activity itself is not enough for quality force estimation. Therefore the MU twitch force technique was introduced as an advanced technique. It performs an automatic sEMG decomposition to obtain all active MUs and their firing moments, enabling us to differentiate between MU recruitment principle and firing rate modulation principle. Forces of all active MUs can be estimated separately, as each MU has assigned its own MU twitch.

Another important feature of MU twitch force technique is that estimation error does not increase with an increased contraction level, as it is the case with activity index. This can be explained by the fact that the compensation of activity index decreases when the force increases. At higher contraction levels, the number of active MUs is increased and the system from Eq. (2) becomes underdetermined, thus producing low-quality activity index. On the contrary, the decomposition results are always IPTs, only the number of decomposed MUs varies at different contraction levels.

Our results show that force estimation using activity index is the fastest, being five times faster than MUAP rate and three times faster than twitch force technique, on average. The most of the time at twitch force technique is spent for the decomposition process, while other steps are completed in less than a second. However, none of the compared methods is able to estimate force in real time, the closest is the activity index, so it should be used where the speed is of the prime importance.

SEMG-based muscle force estimation has unlimited potentials in various applications since surface electrodes are non-invasive, easy to set up and medical supervision is not needed. One of the possible applications is in EMG-driven limb prosthesis control, where sEMG is already used to control the movement of the prosthesis. If muscle force estimation is added, the limb prosthesis could also produce the right force, for example proper grasp force of hand prosthesis.

Other fields that could benefit from the sEMG-based force estimation are rehabilitation and sports. In rehabilitation the progress of subjects can easily be observed using muscle force estimation, as force of an individual muscle is increasing during the rehabilitation process. When sufficient muscle force output is reached, the rehabilitation process should change or stop, depending on the severity of the injury. Moreover, the complete rehabilitation process can be pre-programmed and all what subjects have to do is to follow the force pattern on the screen. The aspect of muscle force estimation in rehabilitation is very important, as it provides the return information to the patient and the therapist.

In sports training at the right intensity is essential to develop some task-dependent skills. Muscle force estimation can provide an insight into the training intensity and therefore act as prevention to overtraining or training at the wrong intensity, and the consequences are quicker progress and fewer injuries of the athletes.

5 Conclusion

In this paper a novel technique for muscle force estimation, called MU twitch force technique, was introduced and compared to the MUAP rate and activity index methods. All three methods are based on motor control information rather than amplitude processing approach, but the way how this information is extracted from sEMG differs significantly. The MUAP rate and activity index methods are indicators of global muscle activity which is correlated to exerted muscle force, but MU twitch force technique goes one step further, as it estimates the activity of each individual MU. This way, a better insight into muscle activity is given and, therefore, a better force estimation is obtained.

To achieve the lowest force estimation error, the execution speed has to be sacrificed. MU twitch force technique performs three times slower than activity index, on average, because a rather complex decomposition of sEMG is included in the method. Nevertheless, it is two times faster than the MUAP rate method.

This work shows the importance of motor control information extraction from sEMG, as this step determines the method performance, so in our future work we will try to estimate the motor control information even better. As it was already mentioned in discussion, our method cannot perform in real-time, so another issue for future research is speed optimization. As sEMG decomposition is the most time consuming part of our method, we will try to eliminate it from our method and to substitute it with another approach that will be able to identify discharge moments of each individual MU without the signal decomposition.

All force estimation techniques used nowadays are performed during isometric muscle contractions. This is the main limitation for practical use of our force estimation method; therefore we will continue to investigate the possibility of muscle force estimation during dynamic muscle contractions.

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